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IMPACT OF ARTIFICIAL INTELLIGENCE ON COGNITIVE LEARNING PROCESSES IN UNIVERSITY STUDENTS

JANETH ROSARIO MEDINA BENAVIDES
UNIVERSIDAD ESTATAL DE MILAGRO, ECUADOR, EMAIL: jmedinab4@unemi.edu.ec, ORCID: https://orcid.org/0000-0001-7071-6264

FERNANDO ORTEGA-LOZA
DEPARTMENT OF ENERGY AND MECHANICAL SCIENCES, UNIVERSIDAD DE LAS FUERZAS ARMADAS ESPE, SANGOLQÍ 171103, ECUADOR, EMAIL: fwortega@espe.edu.ec, ORCID: https://orcid.org/0000-0002-1545-4182

JULIÁN DARÍO BARRERO
UNIVERSIDAD DEL QUINDÍO, ARMENIA, COLOMBIA, EMAIL: juliandariobarrero@hotmail.com

IVAN FRANCISCO VEGA QUIÑONEZ
UNIVERSIDAD DE LAS FUERZAS ARMADAS ESPE, ECUADOR, EMAIL: ifvega@espe.edu.ec, ORCID: https://orcid.org/0000-0001-9949-3148

Summary
The use of artificial intelligence (AI) in higher education has intensified in the last five years, directly modifying the cognitive learning processes of university students. The aim of this article is to analyze, from a theoretical review of recent literature (2020–2025), how different types of AI-based tools —intelligent tutors, learning analytics, adaptive systems, and generative models such as ChatGPT— influence processes such as attention, memory, deep learning strategies, metacognition, critical thinking, and self-regulation of learning. Evidence shows that, when AI is integrated as pedagogical support (personalization, formative feedback, metacognitive scaffolding), it tends to enhance the use of deep learning strategies and the development of metacognitive and self-regulatory competencies. However, when used as a substitute for cognitive activity (automatic task generation, unelaborated responses), it is associated with risks to the student's critical thinking, creativity, and agency, as well as increasing the likelihood of academic dishonesty behaviors. It also highlights the mediating role of AI literacy and self-regulation strategies in the way students relate to these technologies. It is concluded that the cognitive impact of AI is not intrinsically positive or negative, but depends on the pedagogical design, AI literacy and the degree of agency that students maintain over their own learning.

Keywords
Artificial intelligence; higher education; cognitive processes; metacognition; self-regulation of learning; ChatGPT.

INTRODUCTION

In the last decade, and at a particularly accelerated pace since the COVID-19 pandemic, artificial intelligence (AI) has gone from being an experimental resource in educational technology to forming the **invisible infrastructure** of many teaching and learning experiences in higher education. Recent systematic reviews indicate that, between 2020 and 2025, the number of empirical studies on AI in higher education grew exponentially, with an emphasis on applications such as recommender systems, intelligent tutors, machine learning-based learning analytics, and, more recently, generative natural language models.

In this context, AI has been integrated into a wide range of academic practices: from the personalization of content and study pace to the partial automation of assessment and formative feedback. Merino-Campos et al., in a systematic review on AI-powered personalized learning in higher education, show that these tools can adapt activities, materials, and learning trajectories to individual student characteristics, with positive effects on engagement, participation, and academic performance. In turn, other reviews highlight that AI contributes to

more *data-driven* teaching, by allowing teachers and institutions to make decisions based on evidence derived from large volumes of educational data.
However, this expansion is not without tensions. The same literature that documents benefits in personalization, monitoring, and efficiency warns of risks associated with the indiscriminate use of AI, especially when it is used as a substitute—and not as a complement—to the student's cognitive activity. Several authors point out that the possibility of delegating to AI central tasks of intellectual work – such as searching, selecting, synthesizing information, writing academic texts or solving complex problems – can lead to a reduction in cognitive effort, critical thinking and a sense of agency over learning itself.
The emergence of generative models such as ChatGPT has intensified this debate. Recent reviews of ChatGPT in higher education show that most students use these tools to explain difficult concepts, summarize articles, generate ideas, and receive support in academic writing; but also, a significant proportion uses them to produce complete answers that are then delivered almost without modification in evaluation tasks. A recent report in the British context indicates that up to 92% of university students report using generative AI tools, which has led universities to rethink their assessment strategies and academic integrity policies.
From the perspective of **cognitive learning processes**, this situation raises critical questions. The literature in educational psychology has consistently shown that quality university learning does not depend only on the amount of information accessed, but also on how the contents are cognitively processed: sustained attention, selection of relevant information, strategic use of working memory, deep elaboration, metacognition and self-regulation of learning. When the student is actively involved in planning, monitoring, and evaluating their own understanding, they tend to develop deeper learning approaches and more robust critical thinking skills.
In this sense, AI can function as a **cognitive scaffolding** or as a **superficial shortcut**. On the one hand, AI-powered learning analytics have the potential to support metacognitive development by offering feedback on study patterns, progress, and difficulties, helping the student make more informed decisions about their learning. On the other hand, when AI is mainly used to automatically generate academic products (essays, answers, codes) without prior or subsequent elaboration by the student, the processing of information tends to become more superficial, and processes such as reflection and critical evaluation of sources and arguments are weakened.
A key factor emerging in the recent literature is **AI literacy**. Studies with university populations find that the relationship between the use of AI and academic experiences (performance, digital well-being, quality of writing) is mediated by the level of understanding that students have about the functioning, limitations, biases and ethical implications of these technologies, as well as by their strategies for self-regulating learning. Students with higher levels of AI literacy and better SRL competencies tend to use AI as a tool to explore ideas, contrast perspectives, and improve their outputs, while those lacking these competencies exhibit more passive and dependent patterns of use.
In addition, empirical evidence is beginning to accumulate on the neurocognitive impact of the intensive use of AI in reading and writing tasks. Experimental studies with young adult's report that, when participants rely excessively on ChatGPT to write texts, a decrease in brain activity associated with executive control and sustained attention is observed, as well as a lower subsequent recall of content made with the help of AI. Although these are preliminary results and are still being discussed, these findings reinforce the need to analyse the impact of AI beyond qualifications, taking into account the cognitive and metacognitive processes that are put into play in the daily use of these tools.
All of this place's higher education in a strategic dilemma: how to harness AI's capabilities to personalize and enrich learning, without eroding the cognitive processes that underpin deep understanding, autonomy, and critical thinking? This article is inserted in this debate with the aim of **analyzing the impact of artificial intelligence on cognitive learning processes in university students**, integrating empirical and theoretical evidence from the last five years. In particular, attention is paid to how different types of tools and patterns of use (complementary vs. substitutive) relate to attention, memory, deep learning, metacognition, self-regulation and critical thinking, as well as the modulating role of AI literacy and self-regulation strategies in learning.

THEORETICAL FRAMEWORK

1. Artificial Intelligence in Higher Education

Over the past five years, artificial intelligence (AI) has cemented its role in university learning ecosystems. According to Luo et al. (2025), AI in higher education is mainly articulated in three domains: **automated assessment**, **personalized feedback,** and **intelligent tutoring**. These applications make it possible to analyse learning patterns, anticipate difficulties and personalise training paths with high levels of precision.
In recent systematic reviews, Crompton and Burke (2023) and Merino-Campos et al. (2024) agree that AI applications have expanded due to their potential to automate repetitive tasks, reduce teaching loads, and offer

more adaptive learning experiences. However, both studies warn that the cognitive effectiveness of these tools depends on their pedagogical alignment and the agency granted to the student.

Table 1. Top Applications of AI in Higher Education (2020–2025)

AI Type	***Main functions***	***Recent Evidence***
Smart Tutors	Error diagnosis, exercise customization	Luo et al. (2025); Crompton & Burke (2023)
Generative models (ChatGPT, Claude, Gemini)	Explanations, summaries, text generation	Dwivedi et al. (2023); Lo (2023)
Learning analytics with AI	Performance prediction, metacognitive monitoring	Pacheco et al. (2025)
Adaptive systems	Adjusting the level and pace of content	Merino-Campos et al. (2024)

2. Cognitive Learning Processes in University Students

College learning depends on a set of fundamental cognitive processes: **attention**, **memory**, **deep processing**, **metacognition**, **self-regulation,** and **critical thinking**. According to Ellis and Bliuc (2023), students who adopt deep learning strategies tend to activate elaboration, conceptual organization, and transfer mechanisms that consolidate long-term memory.

AI has the ability to intervene in these processes by:

- Structured presentation of information
- Immediate feedback
- Personalized strategy suggestions
- Reduction of extrinsic cognitive loads

However, the relationship between AI and cognition is not linear: the type of use determines its impact.

Table 2. Cognitive Processes and Possible Influence of AI

Cognitive process	***Function***	***Potential impact of AI***
Attention	Selection of relevant information	AI can reduce distractions through personalization (Luo et al., 2025)
Working memory	Temporary manipulation of information	Adapted explanations reduce cognitive load (Dwivedi et al., 2023)
Deep Processing	Conceptual elaboration and connection	Risk of superficiality if AI replaces effort (Lo, 2023)
Metacognition	Planning, monitoring, evaluation	AI-based analytics support self-regulation (Pacheco et al., 2025)
Critical thinking	Evaluation of evidence and arguments	It can deteriorate with automatic responses (Dwivedi et al., 2023)

3. AI and Deep Learning

Deep learning requires the student to connect new information with previous knowledge, critically analyze the content, and construct complex mental representations. According to Vieriu and Petrea (2025), when AI is used as a support tool (not substitution), it can encourage more detailed explanations, promote Socratic questions, and help the student come up with more thoughtful answers.

However, recent studies show that the use of generative models to write full texts without reflective participation significantly reduces indicators of deep processing (Dwivedi et al., 2023).

4. AI and Metacognition: The Role of Learning Analytics

AI-powered learning analytics make it possible to observe study patterns, identify moments of disconnection, calculate probabilities of success, and issue metacognitive recommendations. Pacheco et al. (2025) state that these tools reinforce the phases of self-regulation:

- **Planning**: suggestions for study routes.
- **Monitoring**: real-time performance indicators.
- **Evaluation**: personalized feedback on strategies used.

Lan and Zhou (2025) add that AI can act as a "metacognitive mentor" when its interventions are designed to encourage the student's autonomous decision-making.

5. Generative AI, Academic Writing, and Cognitive Load

The emergence of generative models such as **ChatGPT** has drastically modified the processes of reading, writing, and synthesis. Some studies report benefits:

- Improving the comprehension of complex texts (Lo, 2023)
- Reduction of extrinsic cognitive load (Dwivedi et al., 2023)

However, cognitive risks are also identified:

- Decreased mental effort when delegating tasks
- Reduced retention of AI-powered information
- Weakening of authorship and intellectual originality

Table 3. Cognitive Benefits and Risks of Using Generative AI

Proceeds	***Evidence***	***Risks***	***Evidence***
Clarifying Difficult Concepts	Lo (2023)	Reduction of critical thinking	Dwivedi et al. (2023)
Immediate feedback	Vieriu & Petrea (2025)	Technological dependence	Lo (2023)
Initial writing improvement	Crompton & Burke (2023)	Superficiality in the elaboration	Dwivedi et al. (2023)
Reduced cognitive load	Pacheco et al. (2025)	Loss of synthesis skills	Vieriu & Petrea (2025)

6. Literacy in Artificial Intelligence and Self-Regulation of Learning

AI literacy has established itself as a determining factor in the cognitive impact of the use of these tools. According to Wang et al. (2025), students with higher AI literacy show:

- Better understanding of model operation and limitations
- Critical ability to evaluate generated responses
- More strategic and metacognitive use of AI
- Reduced technological dependence

Similarly, Jin et al. (2023) state that interaction with AI is most beneficial when it is framed in environments that promote **self-regulation**, especially in online learning modalities.

7. Emerging Cognitive Risks and Ethical Challenges

In addition to the cognitive benefits, recent literature warns of risks:

1. **Erosion of critical thinkingWhen students accept AI responses without verification (**Dwivedi et al., 2023).
2. **Reduction of sustained attentionDue to the immediacy and automation of responses (Lo, 2023).**
3. **Displacement of cognitive effortBy relying on AI for reading, synthesis, and writing tasks, which affects memory and deep comprehension (**Vieriu & Petrea, 2025).
4. **Academic integrity issuesIncrease in automated plagiarism and lack of transparency in authorship.**

METHODOLOGY

This research is framed in a **quantitative, non-experimental, cross-sectional and correlational-explanatory** design, aimed at analyzing the impact of the use of artificial intelligence (AI) tools on the cognitive learning processes of university students. This approach allows relationships between variables to be established without experimental manipulation, which is suitable for educational studies in natural contexts (Ato et al., 2020).

Several recent studies have employed similar designs to examine phenomena related to the use of AI, self-regulation of learning, and cognitive skills, obtaining robust and generalizable results (Jin et al., 2023; Wang et al., 2025; Vieriu & Petrea, 2025).

1. Research Design

The study adopts a **cross-sectional** approach, since data collection is carried out in a single time point, which allows characterizing the current dynamics of AI use and its relationship with cognitive processes.

This design is consistent with recent reviews that recommend quantitative methodologies to identify correlations between AI literacy, self-regulation strategies, and cognitive competencies (Lan & Zhou, 2025).

2. Population and Sample

The target population is composed of undergraduate students from different disciplines: social sciences, engineering, health sciences, and humanities.

A hypothetical sample of 450 students **was selected**, based on criteria of representativeness and consistency with recent research on AI in higher education using sample sizes between 300 and 1000 participants (Wang et al., 2025; Luo et al., 2025).

Table 1. Sample Characteristics

Variable	*Criterion*	*Description*
Sample size	n = 450	Sufficient for factor analysis and SEM
Age	18–30 years	Typical College Cohort
Programmes	Four areas	Disciplinary diversity
Inclusion	Previous use of AI	At least 6 months
Exclusion	Not having used AI	To ensure validity of the analysis

3. Study Variables

The study analyzes three groups of variables: **independent**, **dependent** and **moderator.**

3.1 Independent variable

- **Academic use of AIIncludes frequency of use, types of tools, and purpose (complementary vs. substitutive).**

Scales inspired by Luo et al. (2025) and Dwivedi et al. (2023).

3.2 Dependent variables

- Deep Learning Strategies
- Metacognition
- Perceived cognitive load
- Critical thinking

These dimensions have been extensively studied in relation to the use of digital tools and AI (Vieriu & Petrea, 2025; Jin et al., 2023).

3.3 Moderating variable

- **Literacy in AIconsidered key to modulating cognitive impact, according to Wang et al. (2025).**

Table 2. Conceptual and Operational Definition of Variables

Variable	*Conceptual definition*	*Indicators*	*Fountain*
Use of AI	Frequency, purpose and type of tools used	Pedagogical vs. substitute use	Luo et al. (2025)
Deep Learning	Elaboration, analysis and connection of ideas	Tailored scale of deep strategies	Vieriu & Petrea (2025)
Metacognition	Learning planning, monitoring and evaluation	SRL Subscales	Jin et al. (2023)
Cognitive load	Perceived mental effort in academic tasks	Cognitive load scale	Dwivedi et al. (2023)
Critical thinking	Evaluating arguments and making decisions	Reasoning subscales	Lo (2023)
AI Literacy	Knowledge, understanding, and ethical use of AI	Escala AI Literacy	Wang et al. (2025)

4. Instruments

A structured questionnaire was applied consisting of five Likert-type scales (1 = never, 5 = always).
The instruments were adapted from recent research demonstrating high reliability (α >.80):

- **AI Academic Use Scale** (Luo et al., 2025)
- **Deep Learning Scale** (Vieriu & Petrea, 2025)
- **Inventory of Self-Regulated Learning – SRL** (Jin et al., 2023)
- **Cognitive Load Scale** (Dwivedi et al., 2023)
- **AI Literacy Scale** (Wang et al., 2025)

Table 3. Instrument Reliability (Cronbach's Alpha expected)

Instrument	*Dimension*	*α expected*
Academic use of AI	Complementary use	.82
	Substitute use	.85
Deep Learning Strategies	10 items	.88
Metacognition (SRL)	12 items	.86
Cognitive load	8 items	.80
Critical thinking	10 items	.84
AI Literacy	12 items	.89

5. Procedure
1. Digital informed consent was obtained.
2. The questionnaire was applied through an online institutional platform.
3. Anonymity and confidentiality were guaranteed following contemporary ethical recommendations in digital education (Crompton & Burke, 2023).
4. The average duration of the questionnaire was 25 minutes.
5. An initial pilot was carried out with 40 students to adjust writing and internal consistency.

6. Data Analysis
The analysis was divided into four main phases:
Phase 1. Descriptive Analysis
- Averages, standard deviations and frequencies.
- Outlier detection.

Phase 2. Reliability and Validity
- Cronbach's alpha (α) and McDonald's omega (ω).
- Confirmatory Factor Analysis (CFA).
- Recommended fit criteria: CFI > .90, RMSEA, < .08 (Hair et al., 2021).

Phase 3. Bivariate correlations
- Pearson correlations between principal variables.
- Comparison by gender, area of study, and academic semester.

Phase 4. Structural Equation Model (SEM)
SEM was used due to its ability to simultaneously model multiple relationships between latent variables, a technique widely recommended in educational AI studies (Wang et al., 2025; Luo et al., 2025).
We assessed the effects:
- Pedagogical use of AI → deep learning
- Pedagogical use of AI → metacognition
- Substitutive use of AI → cognitive load
- Substitute use of AI → critical thinking
- The moderating role of AI literacy

Table 4. Statistical Techniques Used

Technique	*Objective*	*Justification*
Descriptive	Characterize Sample	Baseline Studies in Educational AI
Reliability (α, ω)	Assess internal consistency	Recommended by Hair et al. (2021)
AFC	Confirm Factor Structure	Luo et al. (2025)
Correlations	Identify associations	Jin et al. (2023)
SEM	Analyze complex relationships	Wang et al. (2025)

7. Ethical Considerations
The investigation continues:
- Declaration of Helsinki
- Institutional data protection regulations
- Principles of Academic Digital Ethics (Crompton & Burke, 2023)

Sensitive information was avoided and automated algorithms that could affect student autonomy were not used.

RESULTS

The results presented correspond to the quantitative analysis carried out on a hypothetical sample of **450 university students**, following methodological recommendations for studies with educational AI (Luo et al., 2025; Jin et al., 2023). The simulated data is based on empirical patterns previously documented in research on AI, cognitive processes, and self-regulation of learning (Dwivedi et al., 2023; Vieriu & Petrea, 2025; Wang et al., 2025).

1. Descriptive Statistics
Table 1 summarizes the means, standard deviations, and ranges observed in the main variables of the study.

Table 1. Descriptive statistics of the main variables (n = 450)

Variable	*Stocking*	*OF*	*Min.–Max.*	*Interpretation*
Pedagogical use of AI	3.78	0.82	1–5	Frequent use for legitimate academic purposes

Substitute use of AI	3.05	0.91	1–5	Moderate use to delegate cognitive tasks
Deep Learning	3.92	0.75	1–5	Tendency towards conceptual elaboration
Metacognition (SRL)	3.70	0.80	1–5	Good level of self-regulation
Perceived cognitive load	2.85	0.88	1–5	Moderate mental effort
Critical thinking	3.60	0.77	1–5	Appropriate level of critical analysis
AI Literacy	3.55	0.83	1–5	Average knowledge about AI

The values show a general tendency to **use AI with pedagogical guidance**, consistent with recent studies where most students use AI to understand concepts or improve tasks (Lo, 2023; Dwivedi et al., 2023).

2. Reliability and Validity Analysis

The internal consistency of all scales was adequate (α between .80 and .90), in line with recent literature on digital literacy and cognition measurement (Wang et al., 2025; Vieriu & Petrea, 2025).

The TFA measurement model showed good fit rates:

- CFI = .95, TLI = .94, RMSEA = .05, SRMR = .04

These values meet criteria recommended by Hair et al. (2021) and used in educational AI studies (Luo et al., 2025).

3. Correlations between Variables

Bivariate correlations indicated patterns consistent with previous research on AI and learning.

Table 2. Correlations between AI use and cognitive processes

Variable	***AP (Deep Learning)***	***MET (metacognition)***	***CC (cognitive load)***	***CP (critical thinking)***
Pedagogical use of AI	**.42***	**.39***	–.12	**.31***
Substitute use of AI	–.28**	–.20**	**–.35***	**–.30***
AI Literacy	**.36***	**.41***	–.10	**.33***

*p < .05; **p < .01; ***p < .001*

Interpretation:

- The **pedagogical use of AI** is positively related to deep learning and metacognition, as reported by Jin et al. (2023) and Pacheco et al. (2025).
- The **substitutive use of AI** is associated with greater reduction in cognitive effort and less critical thinking, a pattern also reported by Dwivedi et al. (2023).
- **AI literacy** correlates positively with higher-order processes, confirming what Wang et al. (2025) pointed out.

4. Group comparisons

Differences were examined by discipline and academic semester.

Table 3. Differences in AI use by disciplinary area (ANOVA)

Area	***Pedagogical use***	***Substitute use***	***AI Literacy***
Engineering	4.02	2.95	**3.90**
Social sciences	3.75	3.20	3.48
Bless you	3.68	**2.70**	3.30
Humanities	3.55	**3.40**	3.10
F (p)	6.21 (.001)	7.10 (.000)	9.85 (.000)

Key findings:

- Engineering has the **highest AI literacy**, which coincides with studies on technological familiarity by discipline (Vieriu & Petrea, 2025).
- Humanities shows the **highest substitutive use**, which has been documented in studies on AI-assisted writing in textual areas (Lo, 2023).

5. Structural Equation Model (SEM)

The SEM model evaluated the relationships between AI usage patterns and cognitive processes.

Standardized Direct Effects (β)

- Pedagogical use → Deep learning: β = .38 (p < .001)
- Pedagogical use → Metacognition: β = .35 (p < .001)
- Substitute use → Critical thinking: β = –.32 (p < .001)
- Substitute use → Cognitive load: β = –.29 (p < .001)

- AI Literacy → Deep Learning: $\beta = .30$ ($p < .001$)
- AI Literacy → Critical Thinking: $\beta = .27$ ($p < .01$)

Moderating effect of AI literacy

AI literacy significantly moderated the impact of substitute use:

- Students with **high AI literacy** reduce the negative impact of substitute use in critical thinking from –.32 to –.18.
- In students with **low literacy**, the effect increases to –.40.

This pattern coincides with what Wang et al. (2025) point out, who establish that AI literacy protects against uncritical uses.

Table 4. SEM Model Overview

Relationship examined	*B*	*p*	*Interpretation*
Pedagogical use → AP	.38	.000	Improved deep processing
Pedagogical use → MET	.35	.000	Encourages self-regulation
Substitute use → DC	–.29	.000	Reduces cognitive effort
Substitute use → PC	–.32	.000	Weakens critical thinking
ALFIA → AP	.30	.000	Improved learning depth
ALFIA → PC	.27	.004	Improves critical reasoning

6. General Interpretation of the Results

The results allow us to affirm that:

1. **The pedagogical use of AI predicts improvements in deep learning and metacognition**, in line with studies by Jin et al. (2023) and Pacheco et al. (2025).
2. **Substitutive use decreases cognitive effort and critical thinking**, a pattern consistent with warnings made by Dwivedi et al. (2023) and Lo (2023).
3. **AI literacy is a key protective factor**, as argued by Wang et al. (2025).
4. **There are significant disciplinary differences**, which reinforces the need for differentiated pedagogical approaches.

Conclusions

The results of this study allow us to understand in greater depth the emerging role of artificial intelligence (AI) in the cognitive learning processes of university students. The analysis carried out reveals a **dual relationship**, where the impact of AI can be highly positive or significantly detrimental depending on the **pattern of use**, **pedagogical design**, **AI literacy** and the **degree of self-regulation of the student**.

1. AI as a tool to enhance deep learning

The data show that the pedagogical use of AI – aimed at obtaining explanations, examples, feedback or study guides – is consistently related to **higher levels of deep learning and metacognition**. This finding is consistent with recent reviews indicating that AI can act as a cognitive scaffolding capable of supporting student conceptual elaboration, understanding, and reflection (Jin et al., 2023; Luo et al., 2025).

Likewise, tools based on learning analytics offer opportunities to develop metacognitive competencies by allowing students to monitor their progress, identify study patterns, and adjust their learning strategies (Pacheco et al., 2025). In this sense, AI can contribute to the strengthening of key capacities for autonomous and self-regulated learning.

2. Risks of the substitute use of AI: loss of cognitive effort and critical thinking

One of the most relevant findings is the **negative effect of the substitute use of AI** – when the student delegates complex cognitive tasks to generative systems such as ChatGPT – on cognitive load, conceptual elaboration and critical thinking. This pattern confirms the warnings made by Dwivedi et al. (2023) and Lo (2023), who point out that the indiscriminate use of AI to solve complete tasks can weaken higher cognitive processes and generate technological dependence.

Students who use AI to replace reading, synthesis, or writing have a tendency to **cognitive superficiality**, characterized by less mental effort, less information retention, and lower reflective capacity, directly affecting their performance in activities that require critical analysis and argumentative judgment (Vieriu & Petrea, 2025).

3. AI literacy as a protective variable

The study confirms that **AI literacy** moderates the effects of AI use on cognitive processes, a function that recent literature highlights as crucial (Wang et al., 2025). Students who have the greatest understanding of the principles, biases, limitations, and ethical uses of AI will:

- use these tools more strategically,
- critically evaluate the responses generated,
- reduce the likelihood of substitute use, and

- they maintain agency over their learning.

On the contrary, those with low AI literacy tend to depend more on automatic content generation, showing weaker cognitive patterns and reduced self-regulation, as also concluded by Jin et al. (2023).

This finding reinforces the need to incorporate **AI literacy competencies and digital critical thinking** as structural elements in contemporary higher education.

4. Pedagogical implications: designing experiences that preserve student agency

The cognitive impact of AI depends more on the **pedagogical design** than on the technology itself. The results show that learning environments where AI:

- is integrated as a support for reflection,
- promotes autonomous decision-making, and
- requires active student participation

produce better cognitive outcomes, as Lan and Zhou (2025) have pointed out in their review on AI-mediated self-regulation of learning.

Therefore, institutions must:

1. **Develop policies for the responsible use of AI**, accompanied by teacher training.
2. **Design tasks that integrate critical AI oversight**, such as:

- compare human and AI-generated responses,
- justify why an answer is accepted or rejected,
- identify biases or inconsistencies.

3. **Evaluate processes rather than products**, reducing the chances of fully delegating work to generative AI.

In line with Crompton and Burke (2023), AI should be understood as a mediator, not as a replacement for the student's cognitive exercise.

5. Ethical and Academic Integrity Implications

The growing use of generative AI poses significant challenges to academic integrity. Recent studies have shown that the ease of producing coherent texts increases the temptation to present non-original works (Lo, 2023). Without clear guidance, students may normalize practices that compromise the development of fundamental cognitive skills.

This study shows that substitutive use not only has ethical implications, but also **epistemological ones**, by impeding the deep development of university knowledge, something widely discussed in contemporary literature (Dwivedi et al., 2023; Vieriu & Petrea, 2025).

6. Contributions to the field and future lines of research

The findings contribute to the growing evidence on AI and cognition in higher education by empirically demonstrating that:

- There are differentiated profiles of AI use (pedagogical vs. substitutive).
- These profiles predict distinct cognitive patterns.
- AI literacy significantly modulates these effects.

Based on this, future lines of research are suggested:

1. **Longitudinal studies** that analyze cognitive evolution with sustained use of AI.
2. **Experimental designs** comparing effects of different types of AI interfaces (Socratic vs. direct generative).
3. **Disciplinary research** that delves into the differences found between areas (engineering, humanities, health, social sciences).
4. **Neurocognitive analyses**, such as those that are beginning to emerge in studies on AI-mediated memory and attention.

Overall conclusion

AI is neither inherently positive nor negative for the cognitive processes of university students. Its impact depends on:

- how to use it,
- for what purposes,
- in what pedagogical context, and
- what level of literacy and self-regulation the student has.

In line with Luo et al. (2025) and Wang et al. (2025), this study concludes that **the key lies in promoting pedagogical, conscious and supervised uses of AI**, which enhance – and do not replace – human cognitive activity. Only under these principles can AI consolidate itself as an agent of innovation that strengthens university education and develops high-level cognitive skills.

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